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A Systematic Analysis of Artificial Intelligence Based Models for Stress Detection

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Abstract:

If stress continues to exist, it can result in a variety of illnesses, physical and psychological. Psychological levels of stress need to be closely assessed to implement prompt and successful early treatment strategies. During the last 10 years, AI based stress detection has drawn a lot of spotlights because of its significance for preventive care and psychological wellness assessment. With an emphasis on data sets, algorithmic procedures and assessment procedures, this statistical study examines developments in stress detection based on AI approaches from 2016 to 2026. This investigation statistically examines developments in deep learning (DL), Machine learning (ML) and hybrid techniques. The findings show a notable trend towards sophisticated neural structures and multi-modal data integration, which improves performance measures. Moreover, variations in assessment processes and data sets standards are also highlighted in this study, which offers a statistical analysis of the state of the art and points out aspects that require more investigation into adaptable as well as dependable stress recognition methods.

Keywords: Artificial intelligence, Machine leaning, Deep learning, Hybrid methods, Stress detection, stress identification models, statistical review

I. Introduction

One of the major psychological and social issues of modern times is stress, leading to an impact on individuals in variety of settings, including work medical centres, educational settings and work environment [1]. By the virtue of the growing pace of technological advancement, digitization, workplace standards, job instability and blurring the boundaries between job and residence, there is a great deal of stress in global society [2]. Sadness, exhaustion, anxiety, heart problems, brain damage and inadequate employment security are just a few of the detrimental effects on physical and psychological well-being that are strongly linked to prolonged interaction with stress [3], [4], [5]. Consequently, academics and professionals have begun to concentrate on managing stress and psychological wellness. Regular clinical tests, interviews and self-assess polls are the conventional techniques used to measure stress [6], [7]. Despite their widespread use, such techniques possess a number of drawbacks, such as failure to record stress patterns in a timely manner, being unable to record stress patterns across a long period, biases in memory and personalization [8], [9], [10]. Additionally, traditional therapies are frequently resource-intensive, aggressive and challenging to extend to significant populations. These restrictions encouraged research into robust, technology-driven systems for ongoing stress monitoring as well as mental health care [11], [12].

AI is now a leading method for stress prediction and detection during the past ten years because of its ability to identify trends in complicated data sets [13]. A fundamental shift in stress and psychological treatment is now feasible due to modern advances in AI, ML and DL systems. The emergence of immediate stress assessment tools has been expedited by the widespread availability of mobile applications and wearable gadgets, which allow uninterrupted gathering and analyzing of data in real-life situations [14]. AI-based methods provide the chance to examine physical metrics including behavioural trends, EEG, electrodermal activity and heartrate fluctuations in order to more accurately gauge the degree of stress, the use of diverse databases as well as context-sensitive analyzes has additionally contributed to the capacity for being adaptive in everyday life [15].

The review's statistical evaluation of AI-driven stress assessment investigation, which prioritizes quantifiable trends in methodology, data sets and performance-based results over qualitative overviews, is what makes this paper unique and novel. The considered strategy in this paper makes it achievable to have greater knowledge of the way various AI methods function in various circumstances and with various forms of data. This study aims to uncover existing patterns and investigate needs by methodically analyzing the development of AI-based stress detection solutions, the main contributions are

- An organized statistical assessment of investigation features
- The detection of constraints that affect the capacity for growth as well as dependability of existing approaches
- A quantitative comparison of methodologies published from last ten years.

II. Methods

A. Data Collection

To assure the openness and repeatability of this review method, this evaluation is carried out in accordance with the PRISMA 2020 criteria [16]. To find appropriate publications on AI-based and integrative platforms for stress detection, an in-depth search of the literature is carried out throughout several digital databases. From 2016 to 2026, searches were conducted in different databases such as Google Scholar, ScienceDirect, Springer, IEEE Xplore, Web of Science, ACM digital Library. To find significant scholarly articles, keywords like “stress detection”, “Deep learning”, “Machine learning”, “Emotion recognition”, “Stress prediction”, “Mental stress”, “Mental health”, “stress detection models” were employed. There was no projected registration of the procedure for this evaluation in an open library. Despite this, the analysis objective, prerequisites for eligibility, data collection procedure and screening approach were all predetermined as part of this review procedure.

B. Inclusion and Exclusion Criteria

The inclusion and exclusion requirements were established to confirm the identification of appropriate and top-notch research for this review. The conference articles, scholarly publication and English-language articles were included. Research that addressed stress identification employing AI algorithms, was presented during 2016 to 2026, and offered test results with quantifiable measures of performance like AUC and accuracy was incorporated. Moreover, to guarantee thorough inspection, research using mental, physical, behavioural and mice data to perform stress identification were also accepted. Similarly, Editorials, opinion articles and scholarly theories lacking empirical findings were all rejected. Additionally, publications with insufficient methodology information and statistical analysis were eliminated. Moreover, articles in which the entire manuscript is not available, studies having a significant likelihood of prejudice, publications having inadequate information for assessing quality and are not in English language are excluded. Papers that weren’t specifically relevant to detection of stress, like broad emotion identification without stress-related evaluation and redundant articles were not included. Furthermore, in order to preserve the paper’s purpose and scope, articles that exclusively relied on non-AI-based models and antiquated methodologies that had no influence on existing AI-based strategies were excluded.

C. Study Selection Procedure

The method used for choosing various studies for this research was organized as well as methodical. Searching databases ultimately turned up 2853 publications. 1064 articles were allowed to remain for abstract and titles verification when redundancies were eliminated. 659 were removed on the basis of relevancy and 147 publications were eliminated after additional review. 258 papers remained from complete text examination after using selection criteria because they lacked test results and had insufficient communication. Lastly, 45 research were chosen to be part of this statistical review. This procedure guarantees the research choosing procedure’s reliability and transparent nature. Figure 1 shows the flow of study selection procedure.

D. Data Collection

Data collection is carried out diligently in this work to gather details collected from every chosen paper. The information gathered consisted of what kind of AI framework utilized, like ML, DL or mixed-method techniques; the kind of data which is fed to the developed model as input, for example behaviour parameters, physical and mental data or multifaceted databases; and the analyzed indicators of performance, which means AUC and accuracy. To facilitate comparison examination, more details about data set properties and real-world usage areas have been complied.

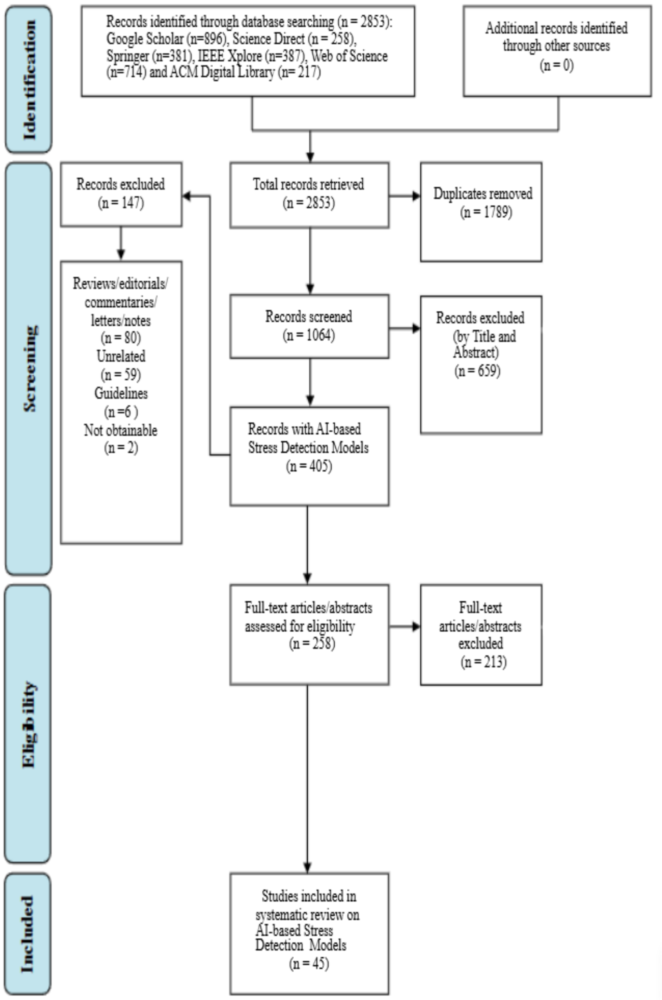

Fig. 1. PRISMA flow chart

III. Ai Approaches For Stress Detection

Over the previous ten years, AI methods for detecting stress advanced dramatically, incorporating a variety of technologies such as conventional ML, DL and hybrid approaches. Hence, this section examines certain AI platforms which have been used to detect stress early and their accurate stress level classification capabilities. Moreover, the quantitative analysis of these models is presented in table I.

The strength of Support Vector Machine (SVM) in processing dimensionally complex data makes it one of the incredibly popular classifiers for stress identification. SVM was employed in a number of research to distinguish between stress degrees. For classification, a study [17] used SVM above other approaches and the method suggested in study [18] yield a 91 percent accuracy in classifying mental stress. Moreover, the flexibility of ML-driven stress identification techniques in different kinds of situations that leads to stress was investigated in research [19] by employing three different approaches such as LDA, KNN and SVM. The findings show that the accuracy of the SVM classifier was the maximum at 95.76%. Another widely used technique for its ability to classify data accurately is Random Forest (RF). In [20] research, the authors employed RF to identify the best feature fusion, which enhances classifier effectiveness in stress detection and achieved 94% accuracy. Moreover, study [21] implemented four different ML algorithms for detecting state of stress in college student and out of them, RF performed better with 84.62% accuracy. Once more, the RF system performed exceptionally well, attaining an accuracy of 97.98 percent in identifying stress in a normal life context [22]. A straightforward supervised classification system, the K-Nearest Neighbour (KNN) method uses closeness to estimate the classification of input units. Study [23] presented a novel method employing KNN to identify human stress during sleep and achieved an astounding 94.37 percent accuracy. Similarly, research work [24] offered an 89.61% classification accuracy of a technique for detecting stress instantaneously using soft keyboard type patterns. Furthermore, KNN based approach to stress detection utilizing physical markers is described by [25] and attained the best accuracy of 98%. A powerful category of ensemble learning techniques, XGBoost-driven stress identification systems use gradient boosting techniques of decision trees to precisely identify stress levels using diverse as well as complicated datasets [26]. An ML method is developed for earlier stress identification, and this method produced an 86% accurate optimized XGBoost system [27]. In this way, applying organized variables taken from context-specific, physical and behavioural data, conventional ML-based stress identification systems tend to exhibit good efficacy in detecting patterns of stress [28, 29, 30].

DL approaches' ability to handle infinite as well as actual-time accumulation of multivariate data collected by wearable gadgets [31], detect irregular relationship between several data formats [32] and produce and classify user-specific features [33], helps them to detect stress effectively. Various DL systems are used in detection of stress which helps in automatically generate structured visualization using unstructured physical indicators and a variety of signals provided by wearable sensors, in contrast to conventional ML algorithms that depend on built-in characteristics [34]. The Gated Recurrent Units (GRU) [35] and Long Short-Term Memory Networks (LSTM) [36] are frequently used to capture time-dependent correlation in periodic physical indicators. Moreover, Convolutional Neural Networks (CNNs) are especially good at identifying layouts in picture data and signal spectral analysis. Study [37] implemented deep 1D CNN and deep MLP neural network for stress identification and classifying emotions, achieved 99.65% accuracy. Moreover, transformer-driven designs [38] and attention methods [39] are established progressively to improve relevancy as well as extended-range relationship modelling. A unique technique presented by [40] improved stress identification and achieved 92.70% accuracy. Research [41] suggested a short-range stress identification technique relying on EEG signals that reaches a 99.25% accuracy rate using CNN as a classifier. Therefore, the DL based systems routinely outperform traditional ML methods in terms of performance.

To increase reliability, understanding and performance in challenging stress situations, hybrid stress identification systems combine several computing approaches [42]. These methods frequently incorporate optimization methods, ML, DL or ensemble learning methodologies with ML or DL systems. Like, study [43] applies the ECNN-LSTM approach for classifying provided data and extracted features using a genetic algorithm. This hybrid methodology assists in anticipating the individual's stages of stress with 99.9% accuracy. Moreover, for stress identification with EEG indicators, research work [44] presented a unique hybrid BDDNet that incorporated DCNN, BiLSTM and DBN which delivered an enhanced accuracy of 97.3 percent. Similarly, [45] suggested a novel design call StressNet, which combines a 2D CNN and LSTM network to identify stress phases using EEG signals and achieved 97.8 percent accuracy. therefore, it can be analyzed that hybrid systems usually work better than solo techniques as these methodologies successfully balance deep feature extraction, attribute optimization and balance comprehension, consequently being ideal for practical stress identification purpose.

Table I: Quantitative Comparison of Existing Stress Detection Models

Reference	Objective	Database	Classifier	Number of Participants	Inputs	Accuracy
Vanitha & Krishnan (2016) [17]	To use EEG data for student stress identification	Self-collected EEG data	Hierarchical SVM	6	EEG signals	89.07%
Han et al. (2017) [20]	To create physical signal-based stress	Self-collected	RF	39	Respiration and ECG	94%

	detector for work-related scenarios					
Kyriakou et al. (2019) [29]	To present a stress detection models using wearable physical sensors	Wearable device dataset	Rule-based algorithm	19	Skin temperature and galvanic skin response	84%
Zhang et al. (2020) [28]	To establish a model for detecting stress in post-traumatic situations using ML	MEG dataset	SVM	50	MEG signals	94%
Li & Liu (2020) [37]	To implement a DL based system which can classify emotions and identify stress levels	WESAD	CNN+MLP	15	Accelerometer, skin temperature, respiration, EMG, EDA and ECG	99.65%
Dham et al. (2021) [30]	To facilitate the identification of emotional stress using AI algorithms and wearable devices	WESAD dataset	Stacking classifier	15	Physical signals	99.92%
Aristizabal et al. (2021) [31]	To assess the viability of stress identification utilizing self-defined metrics and wearable physical data	Empatica E4 device data	Neural Network	16	Heartrate, skin temperature, electrodermal activity	96%
Jegan et al. (2022) [18]	To introduce a stress classification and detection system using SVM	MITBIH multi-parameter	SVM	10	Skin Temperature, GSR and heartrate	91%
Hota & Park (2022) [25]	To create an AI and physical signal-based stress identification methods	WESAD dataset	KNN	40	Electromyogram, heartrate, skin of hands, sweat gland activity and respiration	98%
Hamatta et al. (2022) [43]	To identify mental stress in humans using	DEAP dataset	Genetic algorithm +	32	Galvanic /skin reaction,	99.9%

	hybrid algorithm		ECNN+LSTM		photoplethysmography and EEG	
Sağbaş et al. (2023) [24]	To build an actual time stress identification platform utilizing data from smartphone sensors	Self-collected	KNN	172	Use of phone, Location-driven and GPS-based activity aspects, Gyroscope and movement patterns	89.61%
Anand et al. (2023) [26]	To increase the performance of stress degree detection through ensemble learning methods	Survey data	XGBoost	60	Respiration rate, EDA and heartrate	93.48%
Roy et al. (2023) [35]	To suggest integrated DL algorithm for classifying stress stages and extracting attributes	STEW dataset	CNN+GRU	48	EEG signals	98.10%
Malviya et al. (2023) [36]	To create a DL algorithm that detects mental stress degrees	WESAD	LSTM	15	Accelerometer, Body temperature, Respiration, EDA and ECG	98%
Mane & Shinde (2023) [45]	To suggest a novel design called StressNet to identify stages of stress using EEG signals	DEAP and SEED dataset	DCNN + LSTM	380	EEG signals	97.8%
Su et al., (2024) [21]	To formulate a stress predictor framework for university students	Self-collected	RF	18403	Emotional signals, factors of lifestyle and social, sleep patterns and educational pressure	84.62%
Abd Al-Alim et al. (2024) [22]	To design a framework for detecting stress in real-world settings using ML	SWEET dataset	RF	240	Skin conductance, skin temperature and ECG signals	97.98%
Saddaf Khan et al. (2024) [33]	To formulate technologies for employing intelligent gadgets and	Self-collected	DNN	40	Magnetometers, gyroscopes and accelerometer data	93.50%

	ML approaches to identify monotony and stress behvaior signals in real-time.					
Tanwar et al. (2024) [40]	To offer a wearable technology systems for stress detection using hybrid DL algorithm	WESAD	Attention method	15	Body temperature, EDA and heartrate	92.70%
Attallah et al. (2025) [19]	To investigate the flexibility of ML models in stressful situations	Self-collected EEG data	LDA, KNN and SVM	5	EEG signals	95.76%
Ragavan & Loganayagi, (2025) [23]	To present a novel method to identify human stress during sleep	Kaggle	KNN	10	Heartrate variability, sleep stages and sleep duration	94.37%
Abu-Samah et al. (2025) [27]	To design a ML based method for stress identification in its early phase	Kaggle dataset	XGBoost	15	Stress labels, skin temperature, heartrate, EDA and accelerometer data	86%
Xiang et al. (2025) [32]	To design a multidisciplinary stress detection system using DL	Dryad repository	CNN	15	Skin temperature, heartrate, EDA, accelerometer data	91%
Yang et al. (2025) [34]	To characterize mental stress stages using DL algorithms using heterogeneous physical indicators	WESAD	CNN	15	ECG, EMG, Acceleration, body temperature, respiration, blood volume pulse and EDA	90.96%
Sahare & Dubey (2025) [38]	To provide a thorough structure for identifying stress employing data taken from social networking sites and DL algorithms	Reddit and Twitter data	BERT	5000	Posts and comment from social media	93%

Reddy & Anitha (2025) [39]	To suggest a unique method for using multidimensional data integration to identify mental stress	WESAD, SWELL-KW, bespoke data, student life data	Attention method	183	Context-sensitive, behavioral and physical signals	89.7%
Afify et al. (2025) [41]	To suggest a short-range stress identification method relying on EEG signals	SAM 40	CNN	40	EEG signals	99.25%
Andhare et al. (2025) [44]	To introduce an innovative hybrid BDDNet that uses EEG signals to identify stress	DEAP dataset	DCNN + BiLSTM + DBN	32	EEG signals	97.3%
V. J. & Y. M. (2026) [42]	To develops a hybrid architecture for stress identification for classifying data gathered from internet sites that is associated to stress	Twitter and Reddit data	BERT+RF	1000	Posts from social media	99%

IV. Discussion

According to the review of the published work, it is analyzed that throughout the previous ten years, stress identification techniques have clearly evolved. Initial investigations mostly used conventional ML methods using small data sets, which led to average performance results, but modern advances in hybridization and DL methods have greatly enhanced results, especially in multi-modal environments that includes behavioural and physical data.

Considering such advances, the evaluated research works still have several shortcomings. A lot of research uses tiny or restricted data sets, that restricts how broadly the frameworks may be applied. Furthermore, it is challenging to contrast findings among research work due to the absence of standardized databases and analysis procedures. Unique variations in stress reaction make development of a system even more difficult, making customization and adaptability issues. Such problems emphasize the necessity of standardized assessment systems along with extensive and varied databases.

V. Conclusion

This statistical review shows how AI-driven stress identification has changes dramatically throughout the last ten years, moving from conventional ML systems to sophisticated DL and integrated solutions. Although integrative techniques provide increased performance and resilience, physical signals continue to be trustworthy markers for stress. Even with outstanding results, issues like inadequate standardization and databases constraints still exist. ALL things considered, AI-based stress recognition technologies have a lot of promise for practical uses. To improve the comprehensibility as well as dependability of stress identification models, future investigations need to concentrate on creating standardized heterogeneous databases and included explainable AI algorithms.

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